

Embedded Perception & Decision-making for Safe Navigation in Uncertain, Dynamic and Human-populated Environments

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Embedded Perception & Decision-making for Safe Navigation in Uncertain, Dynamic and Human-populated Environments

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Inria Chroma team & IRT Nanoelec*

Invited Talk – Coboteam Workshop on “Robots Navigation”
France, On-line event, May 28th 2020

Focus on Autonomous Vehicles



Technology status & Ongoing challenges for AVs

- Strong involvement of Car Industry & GAFA + Large media coverage + Increasing Governments supports
- An expected market of 515 B€ at horizon 2035 (~17% world automobile market, Consulting agency AT Kearney, Dec 2017)
- **But Validation & Certification issues are still unclear ... idem for Legal & Regulation issues**

=> Numerous experiments in real traffic conditions since 2010 (Disengagement reports + Insights on system maturity)

=> But still insufficient ... Realistic Simulation & Formal methods are also under development (e.g. EU Enable-S3)



“Self-Driving Taxi Service L3” testing in US (Uber, Waymo) & Singapore (nuTonomy)

- => **Autonomous Mobility Service**, Numerous Sensors + “Safety driver” during testing (take over in case)
- => **Uber**: System testing since 2017, Disengagement every 0.7 miles in 2017 (improved now)
- => **Waymo**: 1st US Self Driving Taxi Service launched in Phoenix in Dec 2018
- => **Disengagement reports provide insights on the technology maturity**

Fatal accidents involving AVs – *Perception failure*

❑ Tesla driver killed in a crash with Autopilot “level 2” active (ADAS mode) – May 2016

- ✓ *The Autopilot failed to detect a white moving truck, with a brightly lit sky (Camera Mobileye + Radar)*
- ✓ *The human driver was not vigilant & didn't took over*



❑ Self-driving Uber L3 vehicle killed a woman

=> *First fatal crash involving a pedestrian*

Tempe, Arizona, March 2018

- ✓ *Despite the presence of multiple sensors (lidars, cameras ...), the perception system failed to detect the pedestrian & didn't disengaged*
- ✓ *The Safety Driver reacted too lately (1s before the crash)*



AVs have to face two main challenges

Challenge 1: The need for Robust, Self-diagnosing & Explainable **Embedded Perception**



Video Scenario:

- The Tesla perception system failed to detect the barriers blocking the left side route
- The driver has to take over and steer the vehicle away from the blocked route (for avoiding the collision)

Video source: AutoPilot Review @ youtube.com

Challenge 2: The need for Understandable **Driving Decisions** (*share the road with human drivers*)

Human drivers actions are determined by a complex set of interdependent factors difficult to model (e.g. intentions, perception, emotions ...)

⇒ Predicting **human driver behaviors** is **inherently uncertain**

⇒ AV have to reason about **uncertain intentions** of the surrounding vehicles



The Lexus SUV, fitted with special sensors, struck the public bus on February 14 in Mountain View, California

Video scenario:

Scene observed by the dash cam of a **bus** moving behind the Waymo AV

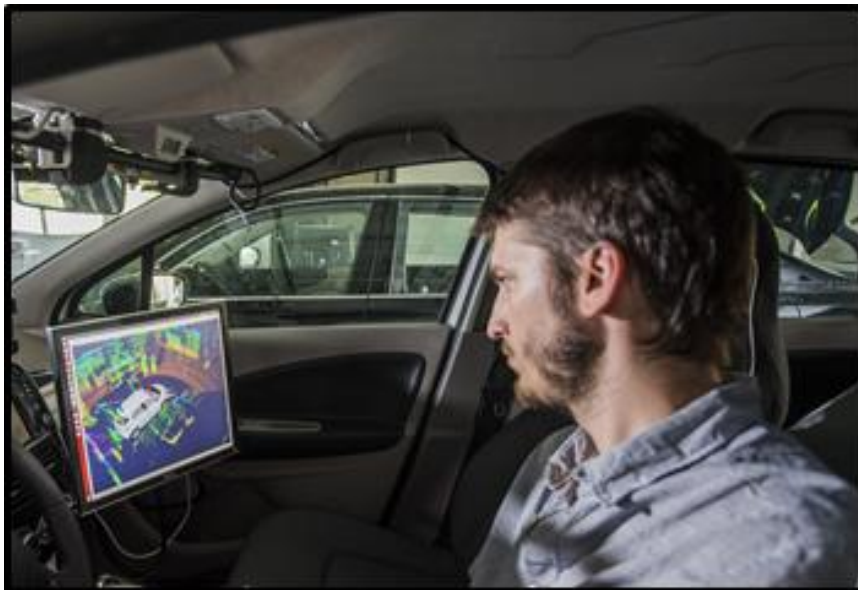
- **Waymo AV** is blocked by an obstacle and it decides to execute a left lane change
- The **bus driver** misunderstood the Tesla's intention and didn't yield
- The two vehicles collided

Video source: The Telegraph

Embedded Bayesian Perception & Decision-making

Main Challenges & Required Technological Breakthrough

- => Robustness, Efficiency, Dynamic Human Environments (Safety is still not guaranteed)*
- => Real-time integration of Perception & Motion planning & Control*
- => Integration into Embedded Hardware & Software (future products)*
- => Validation & Certification*



ADAS & Autonomous Driving

Dynamic Scene Understanding & Navigation Decisions



Situation Awareness & Decision-making

- ⇒ Sensing + Prior knowledge + Interpretation
- ⇒ Selecting appropriate Navigation strategy (planning & control)

ADAS & Autonomous Driving



Embedded Perception & Decision-making for Safe Intentional Navigation

Dealing with unexpected events



Anticipation & Risk Prediction technologies for avoiding upcoming collisions with "something"

- ⇒ High reactivity & reflexive actions
- ⇒ Focus of Attention & Sensing
- ⇒ Collision Risk estimation + Avoidance strategy

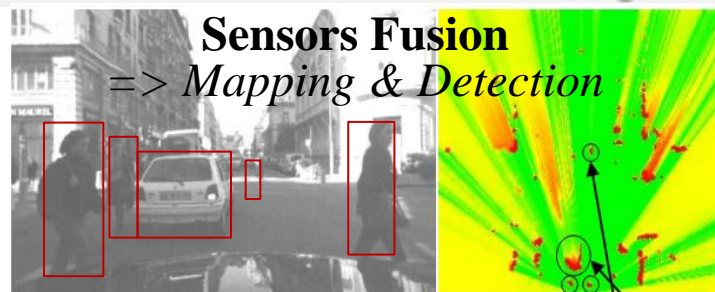
Main features

- ✓ Dynamic & Open Environments ⇒ *Real-time processing & Reactivity (several reasoning levels are required)*
- ✓ Incompleteness & Uncertainty ⇒ *Appropriate Model & Algorithms (probabilistic approaches)*
- ✓ Sensors limitations (no sensor is perfect) ⇒ *Multi-Sensors Fusion*
- ✓ Hardware / Software integration ⇒ *Satisfying Embedded constraints*
- ✓ Human in the loop (mixed traffic) ⇒ *Human Aware Decision-making process (AI based technologies)*
Taking into account Interactions + Behaviors + Social rules (including traffic rules)

1st Paradigm : Embedded Bayesian Perception



Embedded Multi-Sensors Perception
⇒ *Continuous monitoring of the dynamic environment*



❑ Main challenges

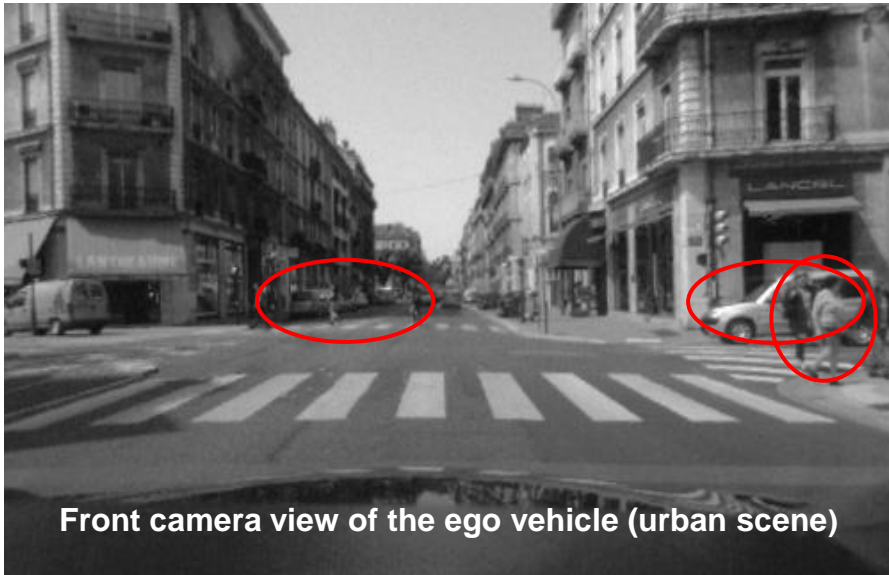
- ✓ *Noisy data, Incompleteness, Dynamicity, Discrete measurements*
- ✓ *Strong Embedded & Real time constraints*

❑ Our Approach: Embedded Bayesian Perception

- ✓ *Reasoning about Uncertainty & Time window (Past & Future events)*
- ✓ *Improving robustness using Bayesian Sensors Fusion*
- ✓ *Interpreting the dynamic scene using Contextual & Semantic information*
- ✓ *Software & Hardware integration using GPU, Multicore, Microcontrollers...*

Dynamic Probabilistic Grid & Bayesian Filtering – *Main Features*

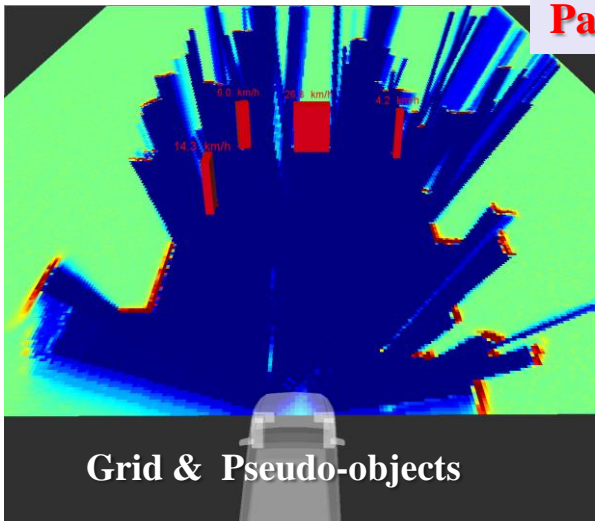
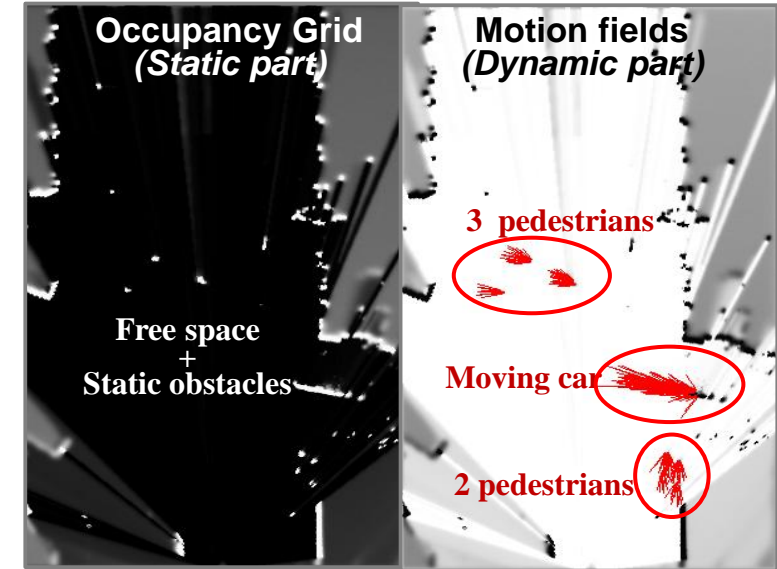
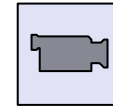
Exploiting the dynamic information for a better understanding of the scene



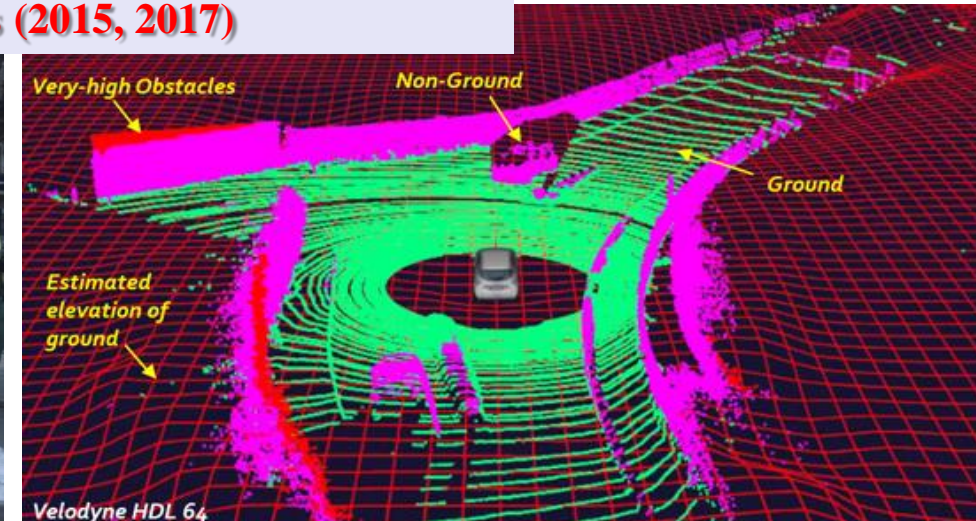
Sensors data fusion
+
Bayesian Filtering
+
Extracted Motion Fields



1st Embedded & Optimized version
(HSBOF, patent 2014)



Patented Improvements & Implementations (2015, 2017)

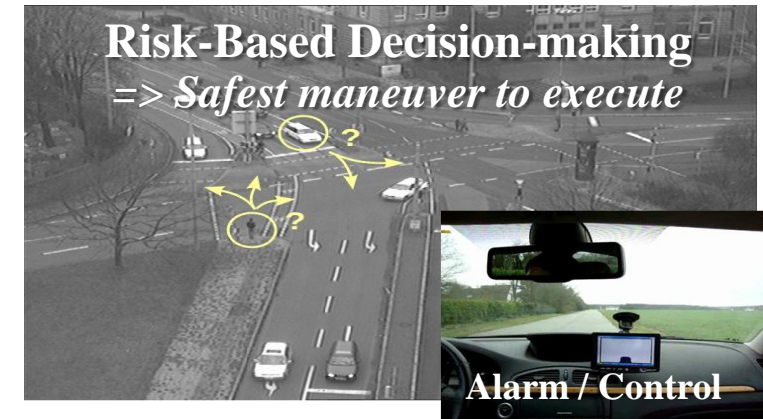
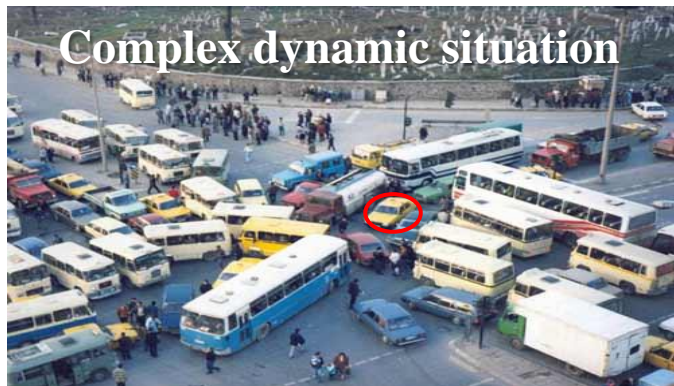


Detection & Tracking + Moving Objects Classification
=> CMCDOT 2015 (including a “Dense Occupancy Tracker”)

Ground Estimation & Point Cloud Classification
(patent 2017)

2nd Paradigm: Collision Risk Assessment & Decision-making

Decision-making for avoiding Pending & Future Collisions



□ Main challenges

Uncertainty, Partial Knowledge, World changes, Real time

Human in the loop + Unexpected events + Navigation Decision based on Perception & Prior Knowledge

□ Approach: *Prediction + Risk Assessment + Bayesian Decision-making*

- ✓ Reason about *Uncertainty & Contextual Knowledge* (using *History & Prediction*)
- ✓ Estimate Probabilistic Collision Risk at a given *time horizon* $t+\delta$ ($\delta = \text{a few seconds}$)
- ✓ Make Driving Decisions by taking into account the *Predicted behavior* of all the observed surrounding traffic participants (cars, cycles, pedestrians ...) & *Social / Traffic rules*

□ Decision-making: *Two types of “collision risk” have to be considered*

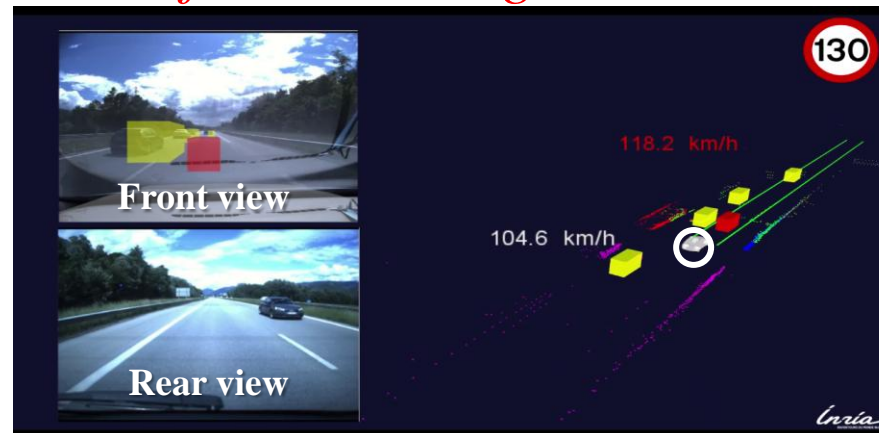
- ✓ *Short-term collision risk* => *Imminent collisions with “something” (unclassified), time horizon $< 3s$, conservative hypotheses*
- ✓ *Long-term collision risk* => *Future potential collisions, horizon $> 3s$, Context + Semantics, Behavior models*

□ Perception level: *Construct “Semantic Grids” using Bayesian Perception & DL*



□ Decision-making level: *Learn driving skills for Autonomous Driving*

- ❖ *1st Step: Modeling Driver Behavior using Inverse Reinforcement Learning (IRL)*
- ❖ *2nd Step: Predict motions of surrounding vehicles & Make Driving Decisions for Ego Vehicle*



4th Paradigm: Combining Motion Planning & Safe navigation

Global planner – Hybrid-State E^*

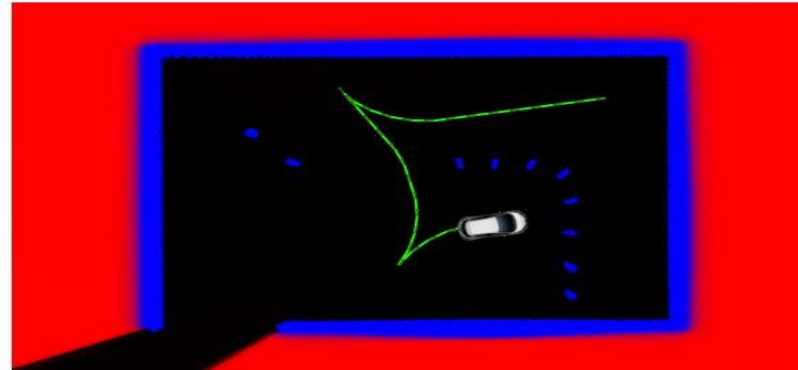
Pros & cons

- + Considers occupancy uncertainty
- + Continuous path even at low resolution
- + Allows complex maneuvers
- + Favors simple maneuvers
- Discrete space representation
- No obstacle motion

Future work

- Use exact vehicle shape
- Online replanning

Example of a computed path



Local planner – DWA

Accuracy

- Accurate trajectory prediction
- Accurate ego vehicle shape

Computing efficiency

- Massively parallel computations over ego vehicle positions and trajectories

Simplicity

- Only simple trajectories
- Short term prediction (5-10s)

Command sampling illustration

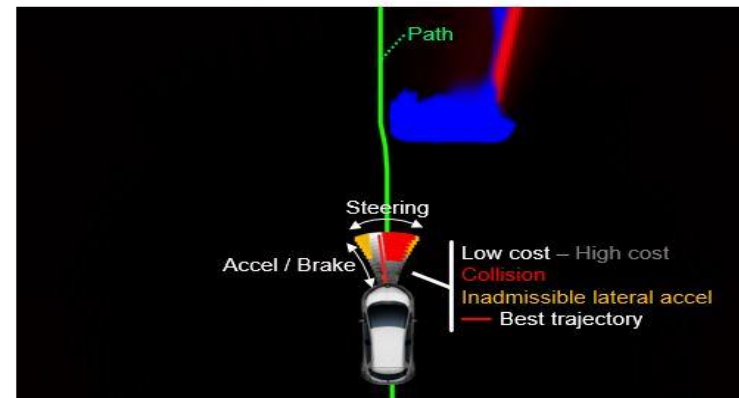


Illustration: Video demos IROS 2018 (Madrid)

